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Automatic generation of document semantics for the e-science Knowledge Grid ☆

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Abstract

This paper proposes an approach to automatically generate semantics for scientific e-documents, and presents its applications in e-document understanding, question answering and question refinement. The approach uses not only keywords and their relations in e-documents, but also the implied meaning of co-occurred keywords that is hard to be exploited, represented and derived by previous semantic representation approaches. The proposed approach facilitates automatic construction, composition, decomposition and derivation of semantics at different granularity levels, which lay the basis for realizing intelligent services of the e-science Knowledge Grid.

Keywords: Fuzzy cognitive map; Document understanding; Semantics; Knowledge Grid; Semantic Web

1. Introduction

The Knowledge Grid is an intelligent interconnection environment that enables people or roles to effectively capture, publish, share and manage knowledge resources. It provides on-demand services to support innovation, cooperative teamwork, problem-solving and decision-making by adopting the technologies developed during work toward the future interconnection environment (Zhuge, 2004b). The e-science Knowledge Grid is an application where scientific documents need to be efficiently processed based on the understanding of content to effectively support scientific activities. The intelligent services of the Knowledge Grid require semantics to be automatically constructed, composed, decomposed and derived at different granularity levels.

Current Semantic Web approaches (Berners-Lee et al., 2001) can help but are not enough to meet these requirements. The XML-based RDF (Resource Description Framework) describes Web resources by using the object-attribute-value model. RDFS (RDF schema) expresses the metadata of Web resources by defining vocabulary, class-based structure, and constraints (Heflin and Hendler, 2001; W3C). SHOE (frame-based Simple HTML Ontology Extensions) supports the Horn clause axioms. OIL (Ontology Inference Layer) supports the description logics and frame. OWL (Web Ontology Language, Smith et al., 2003) describes classes and their relations.

Fuzzy Cognitive Map (FCM) uses adjacency matrix to represent relational knowledge. The reasoning of FCM is realized by matrix operations (Liu and Satur, 1999; Noha and Lee, 2000; Kosko, 1997; Leea and Lee, 2003).

An active document framework (ADF) is a self-representable, self-explainable, and self-executable document mechanism (Zhuge, 2003). It represents document content in four aspects: granularity hierarchy, template hierarchy, background knowledge, and semantic links between fragments.

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Based on the FCM and the idea of ADF, we propose an approach that generates document semantics by considering not only keywords and their relations, but also the implied meaning of co-occurred keywords in documents. Co-occurred keywords imply certain meaning. For example, if the keywords "terrorist", "casualty", "explode" and "panic" co-occur in the same section or paragraph, then the topic about "terror event" is likely to be discussed. The topic determined by multiple co-occurred keywords usually implies rich semantics, further, the meaning of keywords will be specified within the determined topic.

2. The generation of document semantics based on fuzzy cognitive maps

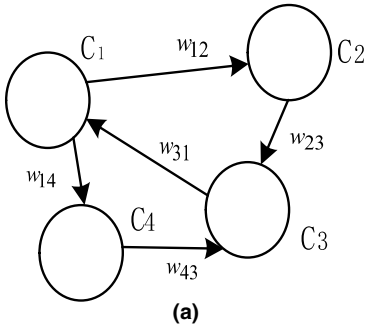
2.1. Fuzzy cognitive maps

The Fuzzy Cognitive Map (FCM) is a graphical model for causal knowledge representation. It can represent not only the causal relations between keywords or phrases but also the knowledge of different granularity levels. An FCM comprises concepts (nodes) and the relations between concepts (arrows). The mathematic model of FCM is as follows (Kosko, 1997):

$$V_{cj}(t+1) = f\left(\sum_{\substack{i=1 \\ i\neq j}}^{N} V_{ci}(t) w_{ij}\right) \quad (1)$$

where V_{ci} and V_{cj} are the state values of the cause concept and the effect concept respectively; w_{ij} is the weight of the causal relation from C_i to C_j. $f(x)$ is the threshold function of concept C_j (this paper uses $\tanh(x)$ function).

Fig. 1(a) illustrates a simple FCM, where C_i is a concept with a state value. The state value can be a fuzzy value within $[0,1]$ that represents the existent degree of a concept, or a bivalent logic in $\{0,1\}$ that represents a concept's open/close state. The weight w_{ij} of an arrow indicates the influence degree from the cause concept C_i to effect concept C_j, which can be a fuzzy value within $[-1,1]$ or a trivalent logic within $\{-1,0,1\}$. If the weight is positive, then the increase/decrease of the value of concept C_i leads to the increase/decrease of the state value of concept C_j. If the weight is negative, the increase/decrease of the state value of concept C_i leads to the decrease/increase of the state value of concept C_j. The adjacency matrix corresponding to the simple FCM is shown in Fig. 1(b).



$$E = \begin{bmatrix} 0 & 0 & w_{31} & 0 \\ w_{12} & 0 & 0 & 0 \\ 0 & w_{23} & 0 & w_{43} \\ w_{14} & 0 & 0 & 0 \end{bmatrix}$$

(b)

Fig. 1. A graphical FCM and its matrix representation.

FCMs have been used in many fields such as Geographic Information Systems (Liu and Satur, 1999), tacit knowledge management (Noha and Lee, 2000), and virtual world (Kosko, 1997).

Documents include not only the cause–effect relations, but also many other relations among concepts. Previous FCMs only support the reasoning of cause–effect relations. We extend the reasoning mechanism of FCM by first deriving out other relations (like sequential or probabilistic causal relations) according to the rules (Zhuge, 2003, 2004a) and the computing model (Zhuge, 2004b) before carrying out the reasoning of FCMs.

2.2. Document semantic templates based on fuzzy cognitive maps

Scientific documents generally include title, abstract, keywords, introduction, body, conclusions and reference. The body part is composed of sections, which further consist of paragraphs or subsections.

Definition 1. *Knowledge point* refers to the basic questions, topics, viewpoints and methods of a domain. A section may have several knowledge points.

For example, "FCM-based document representation", "FCMs' automatic construction" and "FCM-based document understanding" imply three knowledge points.

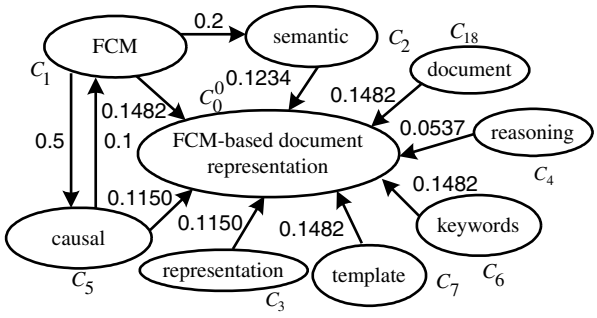
Definition 2. *Theme concept* (denoted as C_i^0) is a special concept of FCM, which reflects the implied meaning of the other co-occurred concepts in the FCM.

For example, C_0^0 is an FCM's theme concept in Fig. 2, which can reflect the implied meaning of these co-occurred keywords (concepts) "FCM", "semantic", "reasoning", "causal", "keywords", "representation", "template" and "document".

Definition 3. *Element semantic template* (denoted as E-FCM) is an FCM that can represent the content of a knowledge point.

According to the definitions of E-FCM and the theme concept, a causal relation exists and directs from theme concept C_j^0 to C_i in reverse while there is a causal relation from the cause concept C_i to the theme concept C_j^0 in E-FCM. For example, E-FCM1 (shown in Fig. 2, E1 is its adjacency matrix) can be represented as Fig. 3 according to the "*reverse*" characteristic of E-FCM.

Definition 4. *Section semantic template* (denoted as S-FCM) is an augmented E-FCM belonging to a section or several paragraphs, which constructs the semantics of a section or several paragraphs.



$$E1 = \begin{vmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1482 & 0 & 0.2 & 0 & 0 & 0.5 & 0 & 0 & 0 \\ 0.1234 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1150 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.0537 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1150 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1482 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1482 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1482 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{vmatrix}$$

Fig. 2. The element semantic template about the knowledge point "FCM-based e-document representation" (denoted as E-FCM1).

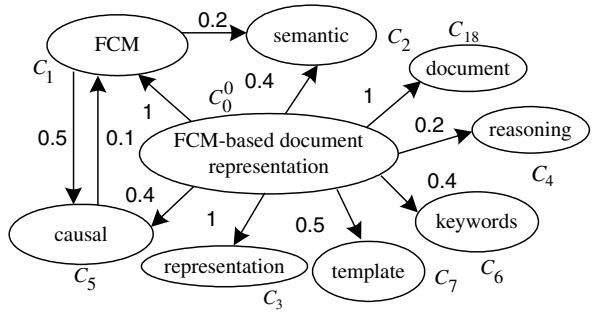


Fig. 3. The FCM formed by reversing the causal relations in E-FCM1.

Fig. 12 is an example of S-FCM.

Definition 5. *Document semantic template* (denoted as D-FCM) is an augmented S-FCM belonging to a document or its body, which generates the semantics of a document or its body.

D-FCM is an integrated pattern for a document. Fig. 14 is an example of D-FCM.

According to the addible characteristic of FCMs, D-FCM can be automatically constructed by combining S-FCMs, and S-FCM can be automatically constructed by combining E-FCMs. So the problem of automatic generation of document semantics is transformed to the problem of automatic construction of E-FCMs.

2.3. Generation of document semantics

The automatic generation process of document semantics is described in Fig. 4. This paper focuses on the gray squares. The candidate document passes the domain keywords repository, if the document belongs to the domain, generates its E-FCMs, S-FCMs and D-FCM. If the document does not belong to the domain, then re-selects the candidate document from the candidate document repository.

The domain keyword repository is constructed as follows:

Step 1. Select documents from the domain and then find their keywords;
Step 2. Recommend these keywords to experts; and,
Step 3. The experts modify these keywords or add some keywords.

2.3.1. Automatic generation of document's element semantic templates

The semantics and content of knowledge points represented by E-FCMs are machine-understandable. E-FCM consists of a theme concept and a set of co-occurred concepts (keywords) that can reflect the content and semantics of the theme concept. The construction criterions of E-FCM are as follows:

Criterion 1. Theme concept in E-FCM corresponds to the title of the training section or paragraphs.

Criterion 2. Concepts in E-FCM correspond to the keywords in a training section or paragraphs, or a set of basic keywords and phrases or keyword repository of this domain.

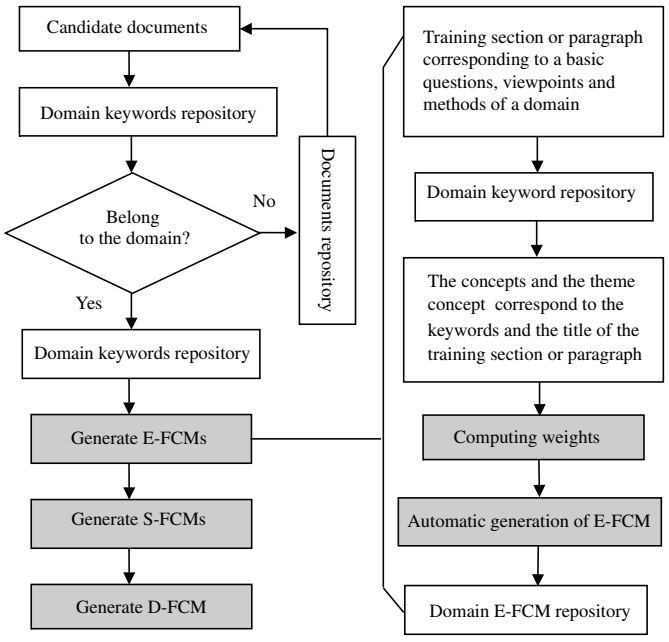


Fig. 4. The process for generating document semantics.

Criterion 3. Relations between concepts in E-FCM correspond to the causal relation between keywords or between keyword and knowledge point in a training section or paragraphs.

Criterion 4. Weights between concepts in E-FCM indicate the degree of one keyword influence on the other keyword or knowledge point in a training section or passage.

For example, Fig. 2 is an E-FCM. E1 is the adjacency matrix of this semantic template.

The construction of E-FCM consists of the following steps:

Step 1. Discover concepts from the keyword repository and candidate document; and,
Step 2. Determine the weights between concepts.

The detailed construction process is described as follows.

2.3.1.1. Determination of concepts in element semantic template. The keywords and relevant phrases of a domain can be regarded as the concepts of E-FCM. According to the construction Criterion 1, the theme concept should be the title of the training section or paragraphs reflecting the knowledge point. If the training section does not contains title, then the user needs to label it. According to Criterion 2, the determination of concepts in E-FCM here is the discovery of appropriate keywords in the training section or paragraphs.

The function of concept C_i's state value can be measured by:

$$V_{ci} = \tanh(x_0/3) \tag{2}$$

where x_0 is the frequency of the keyword, $V_{ci} \in [0,1]$.

According to the reasoning rules, the theme concept C_j^0's state value $V_{c_j^0}$ can be measured by:

$$V_{c_j^0} = \boldsymbol{V} * \boldsymbol{E}(:,j), \tag{3}$$

where V is a set of concepts' state values obtained by reasoning; $\mathbf{E}(:,j)$ is the jth row of the E-FCM's adjacency matrix.

2.3.1.2. Determination of weights in element semantic template. Determination of weights between concepts. Sentences are the basic units to find weights between concepts. Co-occurrence of two keywords in the same sentence implies a certain causal relation. The following formula calculates the weight of the causal relation from concept C_i to C_j:

$$w_{ij} = \sum_{k=1}^{m} b_k/m \tag{4}$$

where m is the frequency of keyword n_i in a training passage; if n_i and another keyword n_j co-occur in the kth sentence, then b_k is 1; otherwise b_k is 0. For example, if "terrorist" and "explode" co-occur 10 times while "terrorist" occurs 20 times in a training passage, then $w_{ij} = 0.5$. At the same time, if "explode" and "terrorist" co-occur 10 times while "explode" occurs 30 times, then $w_{ji} = 0.33$. A small value (e.g., $w_{ij} < 0.04$) implies that there is no relation from C_j to C_i.

Determination of weights between concept and theme concept. If a keyword appeared with a higher frequency than others in a training passage, then it represents a more important concept. Therefore, the weight from concept C_i to theme concept C_j^0 is in proportion to the keyword's frequency. The weight between concept and theme concept can be determined by the following iterative process:

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij} \tag{5}$$

$$\Delta w_{ij} = \eta * V_{ci} \tag{6}$$

$$\sum_i w_{ij} = 1 \tag{7}$$

where η is the learning ratio of weight, and V_{ci} is the state value of concept C_i. The terminative conditions are determined by (1) a large number of iterative times (e.g., more than 500) and (2) $|1 - V * E(:,j)| < 0.01$.

The weights of E-FCMs can also be determined by users or experts.

Determination of relations between E-FCM's weights and parameters. Table 1 shows that the parameter η's influence on E-FCM2's weights is trivial, so the weight determination algorithm is robust.

Table 1
The effects of parameter η influences on E-FCM 's weights

η	0.0005	0.001	0.002	0.003	0.005	0.01	0.02
V_{C22}^0	0.9920	0.9954	0.9954	1.0090	1.0225	1.0225	1.0225
Iterative	272	137	69	47	29	15	8
$w_{1,22}$	0.1331	0.1331	0.1331	0.1332	0.1332	0.1332	0.1332
$w_{4,22}$	0.0490	0.0490	0.0490	0.0489	0.0488	0.0488	0.0488
$w_{6,22}$	0.1331	0.1331	0.1331	0.1332	0.1332	0.1332	0.1332
$w_{7,22}$	0.1331	0.1331	0.1331	0.1332	0.1332	0.1332	0.1332
$w_{24,22}$	0.1331	0.1331	0.1331	0.1332	0.1332	0.1332	0.1332
$w_{25,22}$	0.1056	0.1056	0.1056	0.1056	0.1056	0.1056	0.1056
$w_{26,22}$	0.0490	0.0490	0.0490	0.0489	0.0488	0.0488	0.0488
$w_{29,22}$	0.1308	0.1308	0.1308	0.1308	0.1309	0.1309	0.1309
$w_{30,22}$	0.1331	0.1331	0.1331	0.1331	0.1331	0.1331	0.1331

Table 2
E-FCM2's weights are determined automatically

	C_1	C_4	C_6	C_7	C_{22}^0	C_{24}	C_{25}	C_{26}	C_{29}	C_{30}
C_1	0	0.5	0	0.5	0.1331	0	0	0	0	0
C_4	0	0	0	0	0.0490	0	0	0	0	0
C_6	0	0	0	0	0.1331	0	0	0	0	0
C_7	0	0	0	0	0.1331	0.7	0	0	0	0
C_{22}^0	0	0	0	0	0	0	0	0	0	0
C_{24}	0	0	0	0.7	0.1331	0	0.6	0	0	0
C_{25}	0	0	0	0	0.1056	0.6	0	0	0	0
C_{26}	0	0	0	0	0.0490	0	0	0	0	0
C_{29}	0	0	0	0	0.1308	0	0	0	0	0
C_{30}	0	0	0	0	0.1331	0	0	0	0	0

2.3.1.3. Experiments on the automatic construction of element semantic template. The experiment is to construct the E-FCMs reflecting the knowledge points: "FCM-based complex question automatic answering", "FCM-based e-document representation", "FCMs' automatic construction", "fuzzy cognitive map", "FCM-based scientific e-document understanding" and "FCM-based vague question refining". Here Sections 3.2, 2.2, 2.3, 2.1, 3.1 and 3.3 of this paper are used as training sections to construct the E-FCMs. From the training sections and the keyword repository of the document semantic representation and understanding (denoted as *Domain1*), the E-FCMs weights can be obtained. The weights of "FCM-based complex question automatic answering" are shown in Table 2, and its E-FCM is shown in Fig. 4. Other E-FCMs are shown in Figs. 2 and 5–9 respectively.

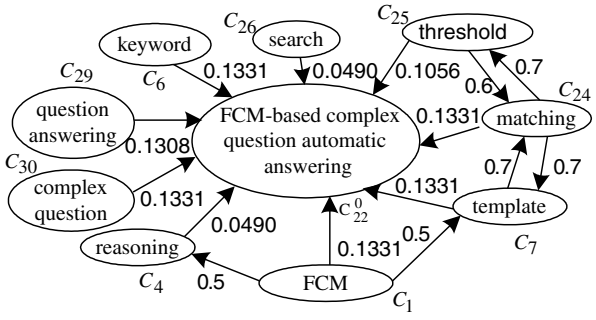


Fig. 5. The element semantic template about the knowledge point "FCM-based complex question automatic answering" (denoted as E-FCM2).

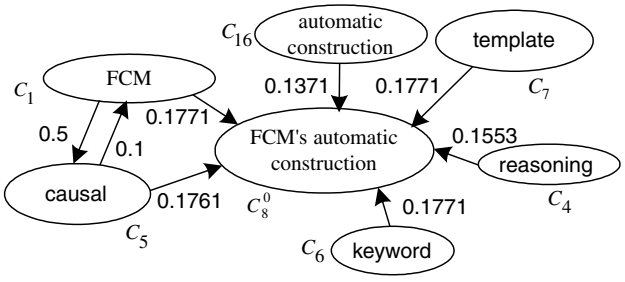


Fig. 6. The element semantic template about the knowledge point "FCMs' automatic construction" (denoted as E-FCM3).

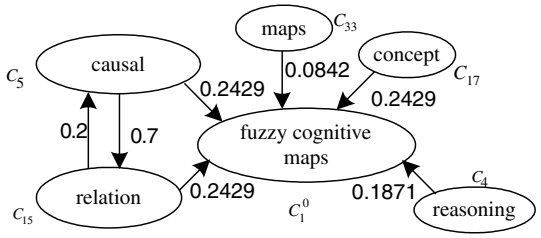


Fig. 7. The element semantic template about the knowledge point "fuzzy cognitive map" (denoted as E-FCM4).

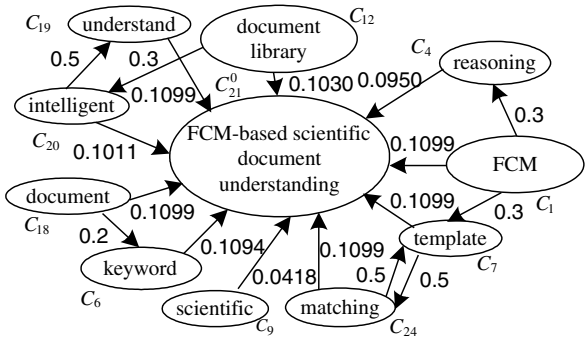


Fig. 8. The element semantic template about the knowledge point "FCM-based scientific document understanding" (denoted as E-FCM5).

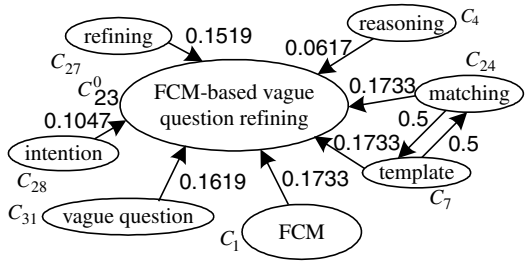


Fig. 9. The element semantic template about the knowledge point "FCM-based vague question refining" (denoted as E-FCM6).

2.3.1.4. Validity of the constructed element semantic templates. Here Sections 1, 2.1–2.4 and 3.1–3.3 are used to verify the validity of E-FCM2 and E-FCM5. The results are shown in Tables 3 and 4. If all the thresholds are 0.85,

Table 3
Reasoning results when using Sections 1, 2.1–2.4 and 3.1–3.3 to verify the validity of E-FCM2

Section	1	2.1	2.2	2.3	2.4	3.1	3.2	3.3
V^0_{C22}	0.5831	0.2118	0.5423	0.6293	0.2283	0.7200	**0.9954**	0.5662

Table 4
Reasoning results when using Sections 1, 2.1–2.4 and 3.1–3.3 to verify the validity of E-FCM5

Section	1	2.1	2.2	2.3	2.4	3.1	3.2	3.3
V^0_{C21}	0.6613	0.1849	0.5874	0.5754	0.2118	**0.9929**	0.7438	0.4816

then Sections 3.2 and 3.1 can be the answer of E-FCM2 and E-FCM5 respectively.

2.3.2. Automatic generation of section semantic template

The section semantic template (S-FCM) is constructed by combining E-FCMs as follows:

Step 1. Combine E-FCMs belonging to a section to form an augmented E-FCM;
Step 2. Delete the concepts that have no direct relations with the other E-FCMs' theme concepts in the augmented E-FCM to form an S-FCM.

Figs. 10 and 11 shows the augmented E-FCM of E-FCM1 (Fig. 2), E-FCM3 (Fig. 6) and E-FCM4 (Fig. 7). S-FCM1 (Fig. 12) is obtained by deleting the redundant concepts, those having no direct relations with the other E-FCMs' theme concepts in the augmented E-FCM. S-FCM1 is machine understandable and expresses the semantics of knowledge points "FCM-based e-document representation", "FCMs automatic construction" and "fuzzy cognitive map", and their relations in Section 2 of this paper. The existence degrees of these knowledge points can be reflected by theme concepts' state values and weights of S-FCM1. The importance of concepts can be determined by

$$V_{ck} = \begin{cases} 1 & \text{if } V'_{ck}(1+\alpha u) \geqslant 1 \\ V'_{ck}(1+\alpha u) & \text{otherwise} \end{cases} \quad (8)$$

where V'_{ck} is the maximal state value of the overlapped concept C_k, u is the times of overlapping, and α is the coefficient measuring overlapping between matrices.

2.3.3. Automatic generation of document semantic templates

The construction of the document semantic template (D-FCM) needs to know the relations and their weights between theme concepts.

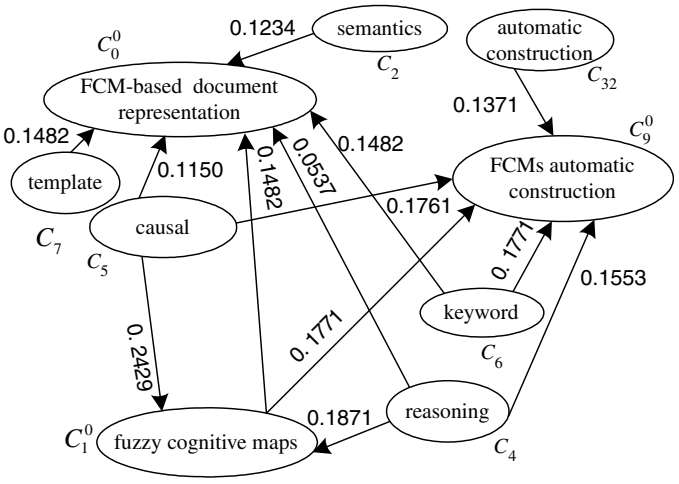


Fig. 11. Augmented E-FCM generated from element semantic template 1 (Fig. 2), element semantic template 3 (Fig. 5) and element semantic template 4 (Fig. 6).

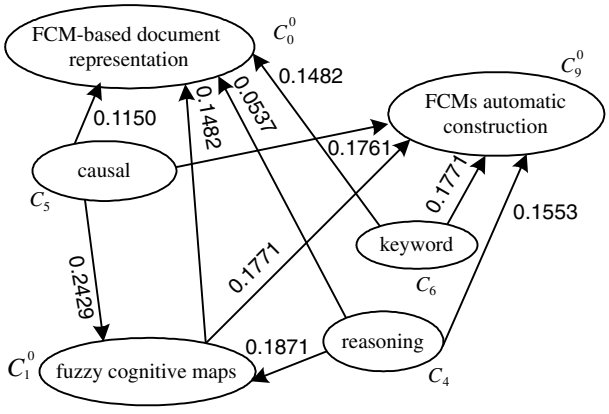


Fig. 12. Section semantic template of Section 2 (S-FCM1).

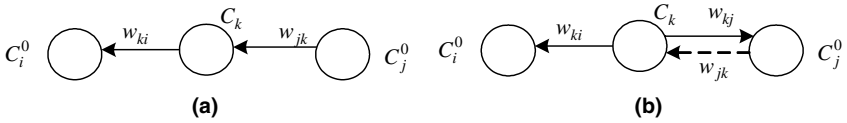


Fig. 10. Relation between theme concepts.

2.3.3.1. Determination of the relations and weights between theme concepts. We use an example to illustrate the basic principle for the determination of relations between theme concepts. There is a concept C_k and two theme concepts C_j^0 and C_i^0 shown in Fig. 10(a), if C_j^0 is a cause of C_k, and C_k is a cause of C_i^0, then there exist causal relations between C_j^0 and C_k as well as between C_k and C_i^0. So there is a causal relation between C_j^0 and C_i^0. On the other hand, if C_k is C_j^0's cause concept shown in Fig. 10(b), then knowing from the "*reverse*" characteristic of the E-FCM, there also exists a causal relation from C_j^0 to C_i^0, since there is a causal relation from C_j^0 to C_k. Therefore, relation between theme concepts can be determined by *reversing* the relation between the fine-granularity concepts.

The weight (T_{ji}) between C_j^0 and C_i^0 can be computed as follows:

$$T_{ji} = \tanh\left(2 * \sum_{k=1}^{N1} \beta_k V_{ck} w_{jk} w_{ki}\right) \quad (9)$$

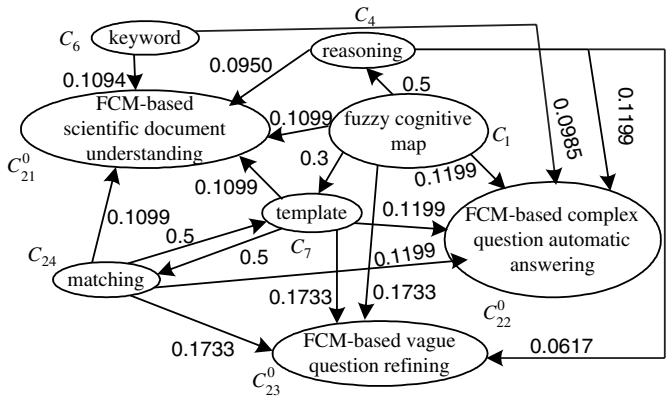


Fig. 13. Section semantic template of Section 3 (S-FCM2).

where $N1$ is the number of concepts that have relations with C_j^0 and C_i^0; β_k is a reversing coefficient of C_k, V_{ck} is the state value of concept C_k, and w_{kj} is the weight between concept C_k and theme concept C_j^0.

2.3.3.2. Algorithm for constructing document semantic template. The construction of D-FCM consists of the following steps:

Step 1. Combine E-FCMs belonging to a section to form S-FCM.
Step 2. Combine S-FCMs belonging to a document to form augmented S-FCM.
Step 3. Calculate weights (T_{ji}) from C_j^0 to C_i^0 in the augmented S-FCM.
Step 4. Delete the concepts that have no direct connection with each theme concept in the augmented S-FCM to form D-FCM.

We take this paper as an example to illustrate the automatic construction process of D-FCM. There are seven subsections in the body part. After each subsection's keywords being matched with E-FCMs in *EFCM-R*1, an E-FCM library that is under the control of *Domain1*.E-FCM1 (Fig. 2), E-FCM3 (Fig. 6), and E-FCM4 (Fig. 7) belong to Section 2, while E-FCM2 (Fig. 5), E-FCM5 (Fig. 8), and E-FCM6 (Fig. 9) belong to Section 3. In steps 1 and 2, S-FCM1 (Fig. 12) and S-FCM2 (Fig. 13) are constructed by combining E-FCM1, E-FCM3 and E-FCM4, and by combing E-FCM2, E-FCM5, and E-FCM6 respectively. D-FCM (Fig. 14) is generated in steps 3 and 4.

D-FCM shows that this paper mainly discusses: "FCM-based document representation", "FCMs' automatic construction", "fuzzy cognitive map", "FCM-based document understanding", "FCM-based complex question automatic answering", "FCM-based vague question refining", and all

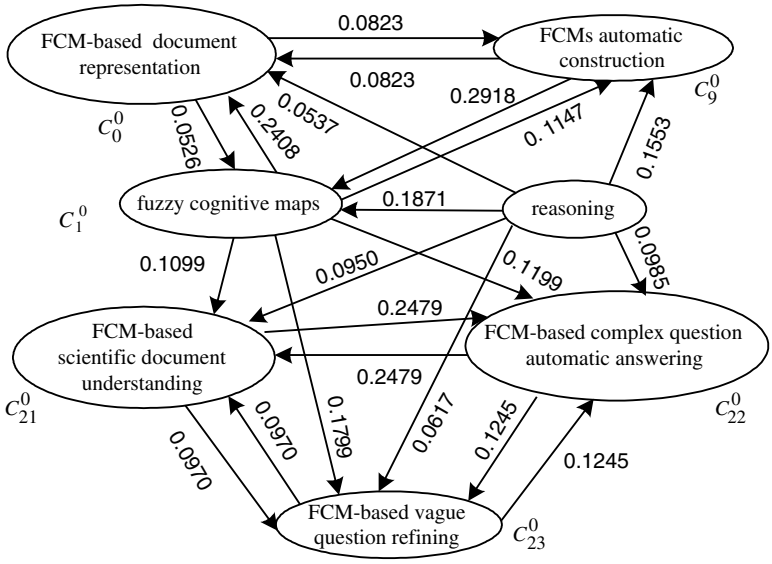


Fig. 14. Document semantic template of this paper.

of these discussions are connected by the basic knowledge points "fuzzy cognitive maps" and the basic keyword "reasoning"; and all the concepts' existent degrees in document are represented by the state values of these concepts. So the D-FCM reflects not only the semantics of knowledge points, relations between concepts, basic knowledge points and basic keywords, but also the existence degrees of these knowledge points in a document.

2.4. Characteristics of the generation of FCM-based document semantics

The proposed approach has the following characteristics:

(1) *Generalized description.* Document can be represented by theme concepts, concepts and their relations at different granularity levels. Using different state values of the same concept, the D-FCM can represent a category of documents.
(2) *Combination of representation and reasoning.* The capability of many classical semantic representation approaches is limited in semantic computation ability. FCM's reasoning can be computed by numeric matrix operations. So the proposed approach can not only represent the semantics of documents with flexibility but also derive out document's content to some extent.
(3) *Robustness.* The approach considers the keywords, their relations and the implied meanings of these co-occurred keywords. So the missing of keywords or relations will not seriously influence on services of the Knowledge Grid.
(4) *Completeness in information retrieval.* If a keyword does not appear in a document, the existent degree of the content reflected by the keyword can be reasoned with these concepts, which have causal relations with it. So our approach can relieve the incompleteness in previous information retrieval approach. Taking Fig. 15 for example, if the "fuzzy cognitive maps" does not exist, then it is difficult for previous IR to do keyword matching. The proposed approach can obtain the state value of the "fuzzy cognitive maps" by FCM reasoning.

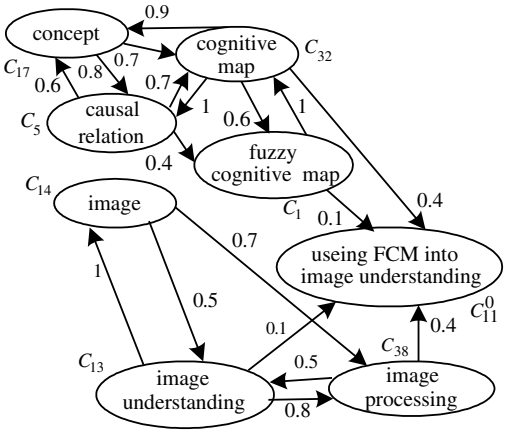


Fig. 15. A semantic template for image understanding.

3. Applications

3.1. Document understanding

Previous document understanding is the process of converting scanned document pages into an electronic and processable form (Altamura et al., 2000). Systems (Hobbs et al., 1988) emphasize on the utility of linguistic information. Our prototype includes an E-FCM repository (denoted as EFCM-R1) that contains eight E-FCMs illustrated in Figs. 2, 5–9, 16 and 17. The keyword set $K1 = \{$"FCM", "intelligent", "information", "document understanding", "vague question", "question answering", "retrieval"$\}$ represents the background knowledge. Threshold values 0.85 and 0.75 are used in the document understanding process and D-FCM's reasoning respectively.

Take this paper (its original structure is shown in Fig. 18) for example, the process of the proposed approach is shown in (Fig. 19). The algorithm of document understanding is as follows:

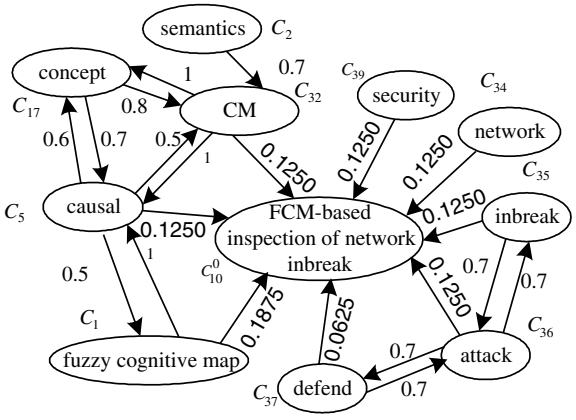


Fig. 16. The element semantic template about the knowledge point "FCM-based inspection of network inbreak" (denoted as E-FCM7).

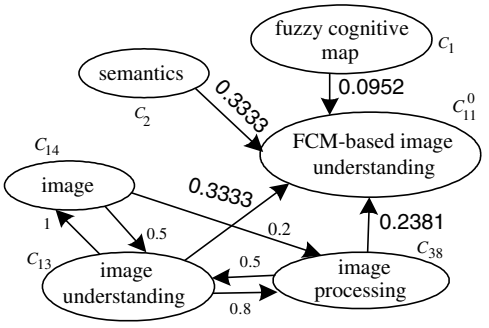


Fig. 17. The element semantic template about the knowledge point "FCM-based image understanding" (denoted as E-FCM8).

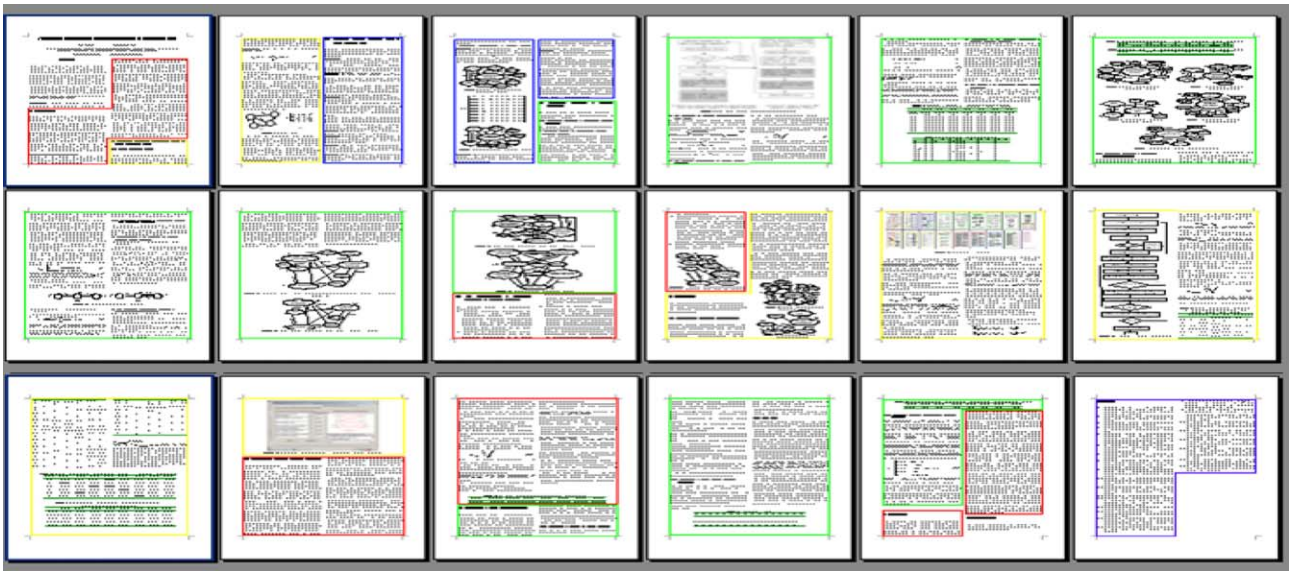


Fig. 18. Original structure of this paper.

Step 1. Get a candidate document from the document repository.

Step 2. Choose an E-FCM repository, for example, EFCM-R1.

Step 3. Get $K1$ and the keyword repository of *Domain1* corresponding to EFCM-R1.

Step 4. Get all the concepts (denoted as TE-keywords) of EFCM-R1.

Step 5. Calculate the degree of document l belonging to domain i as follows:

$$md_{\mathrm{BG}} = \sum_{k=1}^{R} \alpha_k f(x_k)/N \tag{10}$$

where x_k is the frequency of the keyword n_k; $f(x_k)$ is a frequency function of n_k, $f(x_k) = \tanh(x_k/3)$; α_k is the weight of n_k that reflects its important degree in a domain; R and N are the number of the keywords of D_l and K_i respectively. K_i is a set of the keywords that can reflect domain i's background knowledge; D_l is a set of keywords that are the results of matching K_i in document l's title, abstract, keywords, introduction, section heading, conclusion and reference.

In the matching process, it is necessary to match synonymic keywords with the WordNet, and define a compound keywords set to match compound and abbreviation keywords in a domain.

Step 6. If $md_{\mathrm{BG}} \geqslant 0.75$, then go to step 7, otherwise, go to step 2.Here $md_{\mathrm{BG}} = 0.86$. If $md_{\mathrm{BG}} < 0.75$, a new E-FCM repository needs to be selected.

Step 7. Parse the whole paper; sections and subsections are gained.

Step 8. Match TE-keywords in each section.According to Eqs. (2) and (3), the matching degrees between TE-keywords and this paper's subsections are obtained (denoted as Index_i, $i \in (1,2,3,\ldots,9)$). For example, Table 5 shows that Index_2–Index_4 and Index_6–Index_8 correspond to Sections 2.1–2.3, 3.1–3.3.

Step 9. Assign Index_i ($i \in (1,2,3,\ldots,9)$) to the E-FCMs in the EFCM-R1.For example, in Section 2.2, state values of concepts in E-FCM1 and E-FCM2 are $\{V_{c1}, V_{c2}, V_{c3}, V_{c4}, V_{c5}, V_{c6}, V_{c7}, V_{c18}\} = 1.0000$ $\{0.7616\ \ 0.7616\ \ 0.3215\ \ 0.9640\ \ 1.0000\ \ 0.9925\ \ 0.9997\}$ and $\{V_{c1}, V_{c4}, V_{c6}, V_{c7}, V_{c24}, V_{c25}, V_{c26}, V_{c29}, V_{c30}\} = \{1.0000\ \ 0.3215\ \ 0.9925\ \ 0.5828\ \ 0\ \ 0\ \ 0\ \ 0\}$ respectively. In Section 3.2, the concepts' state values of E-FCM1 and E-FCM2 are $\{1.0000\ \ 0\ \ 0\ \ 0\ \ 0.3215\ \ 0.9997\ \ 1.0000\ \ 0.9904\}$ and $\{1.0000\ \ 0.3215\ \ 0.9997\ \ 1.0000\ \ 0.9311\ \ 0.5828\ \ 0.3215\ \ 0.9814\ \ 0.9814\}$ respectively.

Step 10. Match E-FCMs in this paper's sections. Such as, the steps of matching E-FCM1 in Section 2.2 are as follows:

(a) Reason the probabilistic causal relation between C_1 and C_2, C_1 and C_5 respectively;

(b) Reason the concepts' state values of E-FCM1 as follows:

$$\left\{V'_{c_0^0}, V'_{c1}, V'_{c2}, V'_{c3}, V'_{c4}, \ldots, V'_{c18}\right\} = \left\{V_{c_0^0}, V_{c1}, V_{c2}, V_{c3}, V_{c4}, \ldots, V_{c18}\right\} \times E1;$$

(c) According to Eq. (11), calculate the theme concept state value in EFCM-R1.

$$md1_{\text{TE-S}} = V_{c_0^0} \tag{11}$$

(d) Assign Index_i ($i \in (1,2,3,\ldots,9)$) to the concepts of E-FCMs in EFCM-R1.

E-FCM1-8's matching degrees in sections of this paper are been reasoned. Table 6 shows the reasoning results.

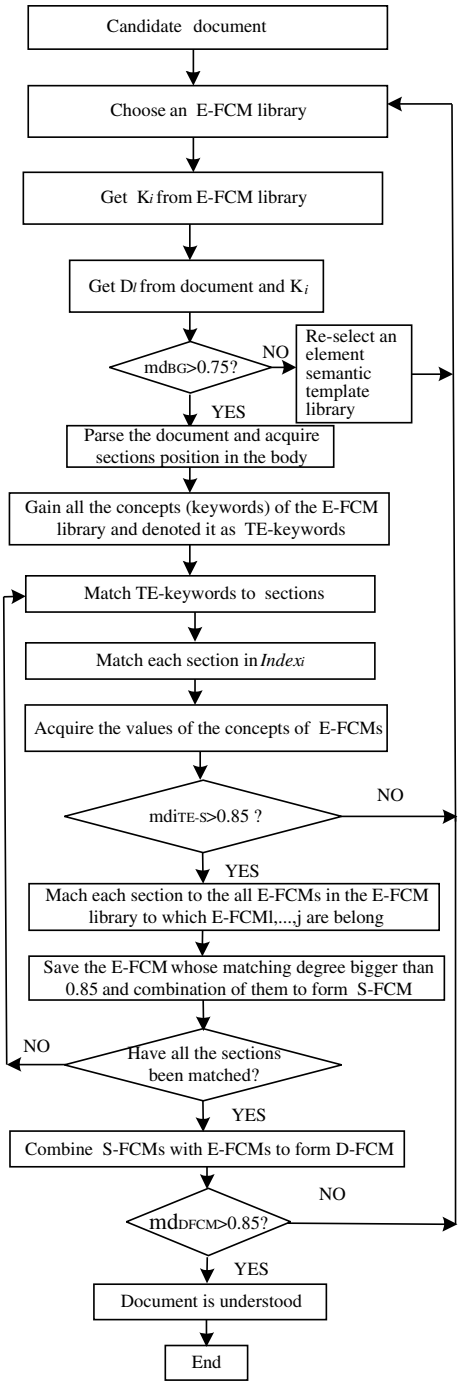


Fig. 19. Flow chart of document understanding.

Table 5
Degrees of matching ($Index_2$–$Index_4$ and $Index_6$–$Index_8$) between TE-keywords and Sections 2.1–2.3 and 3.1–3.3 of this paper

	$Index_2$	$Index_3$	$Index_4$	$Index_6$	$Index_7$	$Index_8$
V_{c1}	0.7616	1.0000	1.0000	1.0000	1.0000	1.0000
V_{c2}	0	0.7616	0	0	0	0
V_{c3}	0	0.7616	0.3215	0	0	0
V_{c4}	0.7616	0.3215	0.8704	0.7616	0.3215	0.3215
V_{c5}	0.9640	0.9640	0.9640	0.3215	0	0
V_{c6}	0	0.9997	1.0000	0.9951	0.9997	0
V_{c7}	0	0.9925	1.0000	1.0000	1.0000	0
V_{c8}	0	0	0	0	0	0
V_{c9}	0.3215	0.5828	0.5828	0.3215	0.9814	0
V_{c10}	0	0	0	0	0	0
V_{c11}	0	0	0	0	0	0
V_{c12}	0	0	0	0.9311	0.3215	0.3215
V_{c13}	0	0	0	0	0	0
V_{c14}	0	0	0	0	0	0
V_{c15}	0.9904	0.7616	1.0000	0.3215	0.3215	0
V_{c16}	0	0	0.9975	0	0	0
V_{c17}	1.0000	0.9975	1.0000	0.9951	0.7616	0.9993
V_{c18}	0.3215	0.9997	0.9311	1.0000	0.9904	0.9640
V_{c19}	0	0	0	0.9997	0.5828	0.5828
V_{c20}	0	0	0	0.7616	0	0
V_{c21}	0	0	0	0	0	0
V_{c22}	0	0	0	0	0	0
V_{c23}	0	0	0	0	0	0
V_{c24}	0	0.5828	0	0.9987	0.9311	0.9904
V_{c25}	0.3215	0	0.5828	0.3215	0.5828	0.5828
V_{c26}	0	0	0	0	0.3215	0.3215
V_{c27}	0	0	0	0	0	0.8701
V_{c28}	0	0	0	0	0	0.5828
V_{c29}	0	0	0	0.5828	0.9814	0
V_{c30}	0	0	0	0	0.9814	0.3215
V_{c31}	0	0	0.3215	0	0	0.9311
V_{c32}	0.9951	1.0000	1.0000	1.0000	1.0000	1.0000
V_{c33}	0	0	0.3215	0	0	0
V_{c34}	0	0	0	0	0	0
V_{c35}	0	0	0	0	0	0
V_{c36}	0	0	0	0	0	0
V_{c37}	0	0	0	0	0	0
V_{c38}	0	0	0	0	0	0
V_{c39}	0	0	0	0	0	0
V_{c40}	0	0	0	0	0	0

Step 11. If $mdi_{\text{TE-S}} > 0.85$, keep this matching degree and the E-FCM; otherwise, delete the E-FCM.

Finally, Sections 2.1–2.3 correspond to E-FCM1, E-FCM 3, E-FCM 4, and Sections 3.1–3.3 correspond to E-FCM2, E-FCM 5, and E-FCM 6 respectively.

If the reference (Zhuge, 2003) (its body includes five sections) is chosen from the document reposi-

Table 6
Degrees of matching between element semantic template 1–8 and Sections 2.1–2.3 and 3.1–3.3

Section	E-FCM	E-FCM	E-FCM	E-FCM	E-FCM	E-FCM	E-FCM	E-FCM
2.1	0.3392	0.2118	0.4393	**0.9911**	0.1849	0.1799	0.3984	0.2762
2.2	**0.9958**	0.5423	0.7646	0.7288	0.5874	0.4960	0.4273	0.0973
2.3	0.7924	0.6293	**0.9903**	**0.8994**	0.5754	0.4810	0.4531	0.3591
3.1	0.6678	0.7200	0.7388	0.5665	**0.9929**	0.5700	0.3709	0.0973
3.2	0.5978	**0.9954**	0.6132	0.3427	0.7438	0.5426	0.2957	0.0973
3.3	0.4484	0.5662	0.4345	0.3056	0.4816	**0.9945**	0.3236	0.0973

Table 7
Degrees of matching between E-FCM1-8 and Section 2–6 of Zhuge (2003)

	E-FCM1	E-FCM2	E-FCM3	E-FCM4	E-FCM5	E-FCM6	E-FCM7	E-FCM8
Section 2	0.1751	0.1137	0.1950	0.2105	0.2164	0.1446	0.1257	0.2032
Section 3	0.1887	0.1149	0.2034	0.1149	0.1299	0.0000	0.0000	0.2030
Section 4	0.1800	0.1128	0.1891	0.1514	0.1498	0.1096	0.1257	0.1951
Section 5	0.1849	0.1129	0.1891	0.1473	0.1257	0.0000	0.0000	0.2084
Section 6	0.1865	0.1137	0.2468	0.2398	0.2423	0.1128	0.0000	0.1800

tory, then matching degrees between the body's Sections 2–6 and E-FCM1-8 are shown in Table 7. It also shows that the understanding system needs to select a new E-FCM repository or document.

Step 12. If all the E-FCMs have been matched, go to step 13; otherwise, go to step 10.

Step 13. Apply E-FCMs' adjacency matrixes to construct S-FCMs.

Step 14. If all the sections have been scanned, go to step 15; otherwise, go to step 13.

Step 15. Apply adjacency matrixes of S-FCMs to construct D-FCM (Fig. 13).

Step 16. Reason on D-FCM, and calculate the matching degree between D-FCM and this paper according to Eq. (12):

$$md_{\text{D-FCM}} = \sum_{i=1}^{k} V_{c_i^0}/k \tag{12}$$

where k is the number of the theme concepts in D-FCM; $V_{c_i^0}$ is the theme concept's state value after doing one time reasoning on D-FCM. This paper's $md_{\text{D-FCM}}$ is 0.9959.

Step 17. If $md_{\text{D-FCM}} > 0.85$, then the D-FCM corresponding to the document and its concepts as well as the state values are recommended to users; otherwise, go to step 2. Fig. 20 is one interface representing the final understanding of this paper. It is suitable for machine understanding so can support intelligent services.

3.2. Question answering

Previous question answering (QA) system needs to identify the question keywords that determine the expected answer type (Webber, 1987; Pasca and Harabagiu, 2001). Recent question answering systems (Voorhees, 2001)

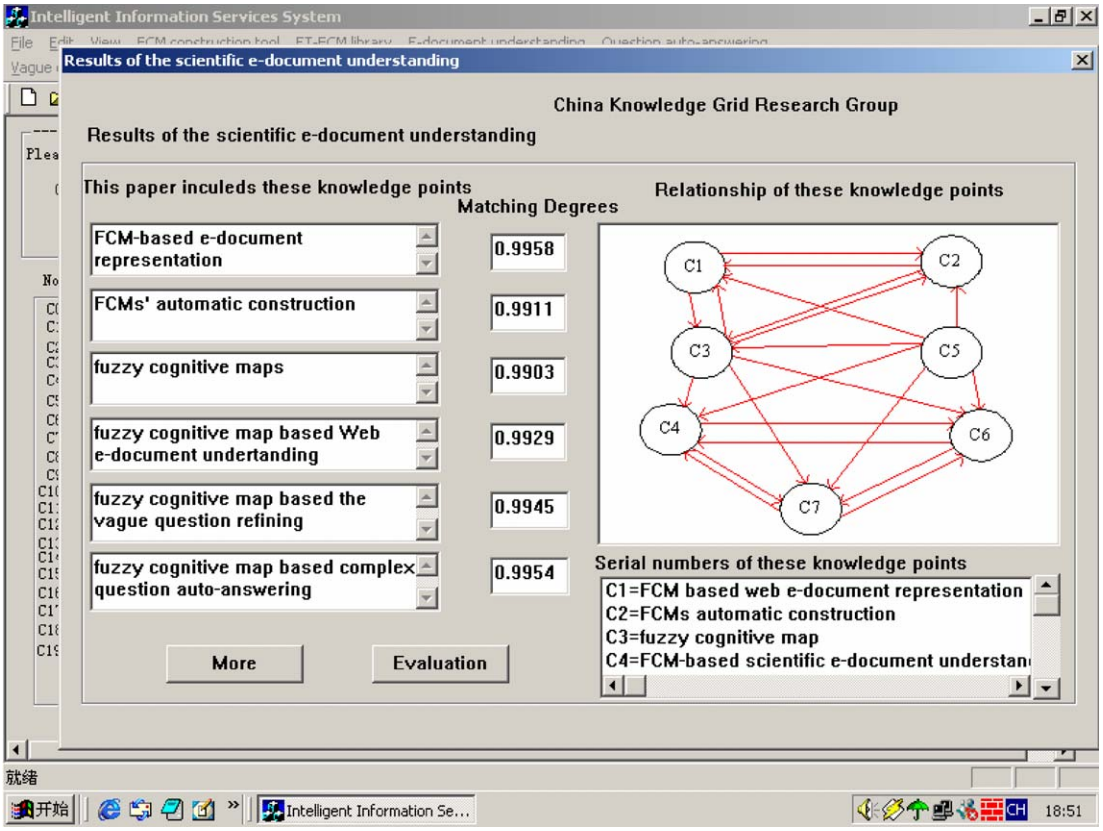


Fig. 20. Interface for displaying document understanding.

requires *sophisticated linguistic knowledge* or tools, such as named-entity recognizer, ontology and WordNet. In TREC10 QA track, the best performing system used many textual patterns (Soubbotin and Soubbotin, 2001). The power of textual patterns for question answering looks quite amazing. But the patterns were *compiled manually based on human analysis of a large set of questions* (Sasaki et al., 2004). Most of the question answering taxonomies and textual patterns in these QA systems (Voorhees, 2001) are based on fine-granularity level, such as keywords and phrases, and the question answering taxonomies and textual patterns are constructed *manually*.

Unlike other passage-retrieval algorithms, we use FCM semantic templates to select documents, sections or paragraphs that may contain the answer within a corpus and can generate and represent the question focus and the question keywords. A complex scientific question generally involves several knowledge points. Given a scientific question, the sentence of the question is firstly parsed to keywords, which are then matched in the theme concepts' keywords in different E-FCM libraries. Following that, the selected E-FCMs are used to find a closely related section or paragraph from the document. Finally, the S-FCMs corresponding to the closely related sections or paragraphs of the document and its D-FCM are recommended to users for the detailed explanation. Of course, we can reorganize the selected sections or paragraphs coming from different documents as the detailed answer. The process of question answering is illustrated by an example as follows:

Step 1. Input question "How to represent and understand document with FCMs?";

Step 2. Get the question's keyword set $Q_k = \{$"represent", "understand", "scientific", "document", "FCM"$\}$ from the question;

Step 3. Compute the matching degree between Q_k and the theme concepts in different E-FCM repositories by:

(a) matching Q_k with the theme concepts in different E-FCM repositories, e.g., the results of matching Q_k in EFCM-R1 are shown in Table 8, where $md_i = p/k$, k is the number of the theme concept keywords, and p is the number of theme concept keywords in Q_k;

(b) computing the matching degree between Q_k and EFCM-R1 as follows:

$$md_{Qk} = \sum_{i=1}^{g} q_i/g \tag{13}$$

where q_i is the md_i that is bigger than 0.5, and g is the number of md_i that is bigger than 0.5.

In the matching process, it is necessary to use WordNet to match the synonyms, and define a keywords repository to match the compound and abbreviation keywords in a domain.

Step 4. Choose the E-FCM repository corresponding to the maximum md_{Qk}. In this case, EFCM-R1 is selected;

Step 5. Get K_1 and the keyword repository of *Domain1*, which correspond to EFCM-R1;

Step 6. Get the TE-keywords of EFCM-R1;

Step 7. Get a document (e.g., this paper) from document repository;

Step 8. Select the E-FCMs whose md_i is bigger than 0.50 in EFCM-R1. Here E-FCM1 and E-FCM 5 are selected;

Step 9. Match TE-keywords in each subsection, then Index_i ($i \in (1,2,3,\ldots,9)$) are obtained;

Step 10. The matching degrees between Index_2–Index_4, Index_5–Index_8 and Sections 2.1–2.3 and 3.1–3.3 are shown in Table 6.
Table 6 shows that E-FCM1 corresponds to Section 2.2; E-FCM5 corresponds to Section 3.1. Therefore, this paper can be recommended to the user who asks. If the matching degree is less than the threshold, another document will be selected from the document repository and then go to step 7;

Step 11. Assign Index_i ($i \in (1,2,3,\ldots,9)$) to the E-FCMs in EFCM-R1 and select the matched E-FCMs, that is, searching for knowledge points related to E-FCM1 and 5. Here, E-FCM 1-6 are selected.

Step 12. Using E-FCM1-6 to understand the selected paper; S-FCM1 (Fig. 12), S-FCM2 (Fig. 13) and D-FCM (Fig. 14) are acquired;

Step 13. If $md_{\text{D-FCM}} \geqslant 0.85$, display the sections or paragraphs corresponding to the S-FCMs to the user as a succinct answer for the question; recommend D-FCM and this paper to the user as the detailed answer to the question; otherwise, go to step 7.

The above algorithm can handle erroneous and avoid sophisticated linguistic issues.

3.3. Vague question refining

Sometimes users are unable to exactly express their intentions with words or questions. The FCM-template-based vague question refinement system works this way to help users: recommend some candidate documents first for review, then a user can select one or more documents, sections or paragraphs from the candidates to express

Table 8
The results of match Q_k in the EFCM-R1's theme concepts

E-FCM1	E-FCM2	E-FCM3	E-FCM4	E-FCM5	E-FCM6	E-FCM7	E-FCM8
$md_1 = 75\%$	$md_2 = 33\%$	$md_3 = 20\%$	$md_4 = 33\%$	$md_5 = 100\%$	$md_6 = 33\%$	$md_7 = 33\%$	$md_8 = 50\%$

his/her interest roughly. Next, combine the E-FCMs corresponding to the selected passages and delete the concepts with the lowest frequency, and then the maintained concepts are matched in the E-FCMs. The E-FCMs whose matching degrees are bigger than a threshold are selected as the next matching templates. With the recommended templates, more related documents are retrieved as candidates for the next round. A user's vague question can be gradually refined until the user is satisfied with the answer.

3.3.1. Algorithm 1: Refining the vague question

Step 1. A user selects documents, sections or paragraphs from the candidates.
Step 2. Choose K_j corresponding to E-FCM library obtained from the selected documents.
Step 3. Match K_j in selected document's title, abstract, keywords, introduction, section heading, conclusion and references, then D_i is obtained.
Step 4. If $md_{BG} \geqslant 0.75$, then go to step 5, otherwise, a new E-FCM library needs to be selected, then go to step 2.
Step 5. According to K_j, get the document's E-FCM library.
Step 6. Understand the document in the selected E-FCM library.
Step 7. Save the E-FCMs as the results of the document understanding.
Step 8. Have all the documents chosen by the user been understood? If not, go to step 3; otherwise go to step 9.
Step 9. Acquire the selected E-FCMs' concepts (denoted as TE-keywords).
Step 10. Use the element semantic template selection algorithm to save E-FCMs.
Step 11. Re-match the saved E-FCMs in documents and obtain more related documents.
Step 12. Recommend the more related documents to a user; if the user is not satisfied, go to step 1; otherwise, go to step 13.
Step 13. Transform the E-FCMs with which a user is satisfied with the easy-to-understand format, and then recommend them to the user (e.g., in the form of Fig. 20).

The key problem involved in the vague question refinement algorithm is for selecting appropriate E-FCMs.

3.3.2. Algorithm 2: the element semantic template selection

Step 1. Obtain the set of concepts (e.g., $Cs = \{C_i, \ldots, C_j, \ldots\}$) in the selected E-FCMs;
Step 2. Calculate the frequency of each concept in Cs (the frequency set is denoted as $NubCs = \{n, \ldots, k, \ldots\}$);
Step 3. Delete the concepts whose frequency is the lowest, and then a new set of E-FCM's concepts is obtained (denoted as $NCs = \{C_p, \ldots, C_f, \ldots\}$);
Step 4. Calculate the ratio of each E-FCM's concepts in the NCs;
Step 5. If the ratio is bigger than the threshold, then save the E-FCM, otherwise delete it;
Step 6. If all of the E-FCMs have not been calculated, go to step 4; otherwise go to step 7;
Step 7. Take all the maintained E-FCMs as the semantic templates for the next document matching.

3.3.3. Case study

To illustrate the above algorithm, a case study is carried out as follows. Firstly, the user selects a set of documents recommended by the document repository. The E-FCMs corresponding to the selected documents are E-FCM1-8. By using these E-FCMs as matching templates, more related documents are recommended to users. Thus, the second loop starts. The user selects documents or sections again; the corresponding E-FCMs are processed and filtered to get the appropriate E-FCMs (E-FCM1-6), as shown in Figs. 2 and 5–9. Using the E-FCMs as matching templates to search in the document repository again, e.g., this paper is obtained as the final searching result. Finally, recommend this paper's sections corresponding to S-FCMs or theme concepts of E-FCMs and D-FCM to users as shown in Fig. 20.

This example only considers E-FCM selection computation. It first deletes theme concepts $C_0^0, C_8^0, C_9^0, C_{10}^0, C_{11}^0, C_{21}^0, C_{22}^0$, and C_{23}^0 in E-FCM1-8 then obtains each concept's frequency ($NubCs$) as shown in Table 9. Delete the concepts that have the smallest value to get the result $NCs = \{C_1, C_2, C_3, C_4, C_{12}, C_{17}, C_{18}, C_{24}\}$. The results of matching degrees between the E-FCMs and the NCs are shown in Table 10. If the threshold is set as 0.5, then E-FCM1-6 are reserved. Use these reserved templates to match in the document repository again, and then this paper is obtained as the final matching result. Finally, this paper is recommended in the form of Fig. 20, which intui-

Table 9
The values of *NubCs*

C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
8	3	3	5	4	4	4	1	1	1	1	1	1	1	1	1
C_{24}	C_{25}	C_{26}	C_{27}	C_{28}	C_{29}	C_{30}	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	C_{37}	C_{38}	
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	

Table 10
The degrees of matching between selected element semantic templates and *NCs*

E-FCM1	E-FCM2	E-FCM3	E-FCM4	E-FCM5	E-FCM6	E-FCM7	E-FCM8
100%	56%	100%	60%	67%	50%	30%	40%

tively represents the interests of users. We can further reorganize these selected sections or paragraphs that come from different documents according to the user's interest.

3.3.4. Adaptive threshold determination of theme concepts

The determination of C_i^0's threshold θ_i is a key issue. If $V_{c_i^0} > \theta_i$, the knowledge point represented by the semantic template belongs to this section or paragraph. Relations exist between θ_i and the number of the recommended documents as well as their quality in vague question refining or document recommendation. If θ_i is lower/higher, the number of recommended documents are increased/decreased, but the qualities become bad/better consequently. In order to automatically adjust θ_i, the adaptation of the theme concept's threshold is defined as follows:

$$\theta_i = \begin{cases} \theta_i - \Delta & I - N = 0 \\ \theta_i + 2\Delta & f \leqslant -I \\ \theta_i + \Delta & f > -I \text{ and } f \leqslant \delta \\ \theta_i - \Delta & f > \delta \\ \theta_i & \text{otherwise} \end{cases} \quad (14)$$

where $f = 3 * I - N$, Δ is a constant, I is the number of documents or sections relevant to the user's interests, N is the number of documents or sections irrelevant to the user's interests. N and I can also be regarded as the number of keywords (or knowledge points) that represent the user's interest or non-interest. Eq. (14) shows that the document selection is accomplished in the process of automatically adjusting the thresholds of E-FCMs.

4. Conclusions

By defining semantic templates for e-documents of different granularities, this paper proposes an approach to automatically generate semantics for scientific e-documents. The approach uses document's keywords, their relations, and the implied meaning of co-occurred keywords that are hard to be exploited and reasoned by previous semantic representation approaches. The semantics can be constructed, reasoned, composed and decomposed at different granularity levels according to requirement. So it plays an important role in implementing intelligent services based on document understanding in the e-science Knowledge Grid environment.

Given training passages and keyword repository, the understanding can be automatically carried out. The semantic templates enable the question answering mechanism to return a relatively precise and overall answer by avoiding sophisticated linguistic approaches and many manual works for constructing answer taxonomy. The templates also support users to express and refine their intentions by using element semantic templates.

The proposed approach can be extended to support richer semantic relationships and reasoning by combining the semantic link network (Zhuge, 2003, 2004a) with FCM. The reasoning mechanism for the combination model needs to use the semantic link reasoning rules (Zhuge, 2004b). We are exploring relevant mathematic principles.

References

Altamura, O., Esposito, F., et al., 2000. Transforming paper documents into XML format with WISDOM++. International Journal of Document Analysis and Recognition 3 (2), 175–198.

Berners-Lee, T., Hendler, J., Lassila, O., 2001. The semantic Web. Scientific American 284 (5), 34–43.

Heflin, J., Hendler, J., 2001. A portrait of the semantic Web in action. IEEE Intelligent Systems 16 (2), 54–59.

Hobbs, J.P., Sticket, M., et al., 1988. Interpretation as abduction. In: Proceedings of the 26th Annual Meeting of the Association for Computational Linguistics, Buffalo, NY, June, pp. 95–103. Available from: <http://acl.ldc.upenn.edu/P/P88/P88-1012.pdf>.

Kosko, B., 1997. Fuzzy Engineering. Prentice-Hall.

Leea, K.C., Lee, S., 2003. A cognitive maps simulation approach to adjusting the design factors of the electronic commerce Web sites. Expert Systems with Applications 24, 1–11.

Liu, Z.Q., Satur, R., 1999. Contextual fuzzy cognitive maps for decision support in geographic information systems. IEEE Transactions on Fuzzy Systems 7 (10), 495–502.

Pasca, M.A., Harabagiu, S.M., 2001. High performance question/answering. In: Processing of the 24th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 366–374.

Sasaki, Y., Isozaki, H., et al., 2004. NTT's QA systems for NTCIR QAC-1. In: Processing of the Third NTCIR Workshop. Available from: <http://research.nii.ac.jp/ntcir/workshop/OnlineProceedings3/NTCIR3-QAC-SasakiY.pdf>.

Smith, M.K., Welty, C., et al., 2003. OWL Web ontology language guid. Availale from: <http://www.w3.org/tr/2003/WD-owl-guide-20030331/>.

Soubbotin, M.M., Soubbotin, S.M., 2001. Patterns of potential answer expressions as clues to the right answer. In: Proceedings of the 10th Text Retrieval Conference (TREC10), NIST, Gaithersburg, MD, pp. 175–182.

Noha, J.B., Lee, K.C., 2000. A case-based reasoning approach to cognitive maps-driven tacit knowledge management. Expert Systems with Applications 19, 249–259.

Voorhees, E., 2001. Overview of the TREC 2001 question answering track. In: Proceedings of the 10th Text Retrieval Conference (TREC10), NIST, Gaithersburg, MD, pp. 157–165.

W3C. RDFCore Working Group, W3Cpublication. URL Available from: <http://www.w3.org/2001/sw/RDFCore/>.

Webber, B., 1987. Question answering. In: Shapiro, S.,C. (Ed.), Encyclopedia of Artificial Intelligence, vol. 2. Wiley, pp. 814–822.

Zhuge, H., 2003. Active E-document framework ADF: model and tool. Information and Management 41, 87–97.
Zhuge, H., 2004a. Retrieve images by understanding semantic links and clustering image fragments. Journal of Systems and Software 73 (3), 455–466.
Zhuge, H., 2004b. The Knowledge Grid. World Scientific, Singapore.

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